```
!pip install yfinance
!pip install seaborn
!pip install matplotlib
!pip install pandas
!pip install scipy
!pip install statsmodels
!pip install arch
!pip install pmdarima
```

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```

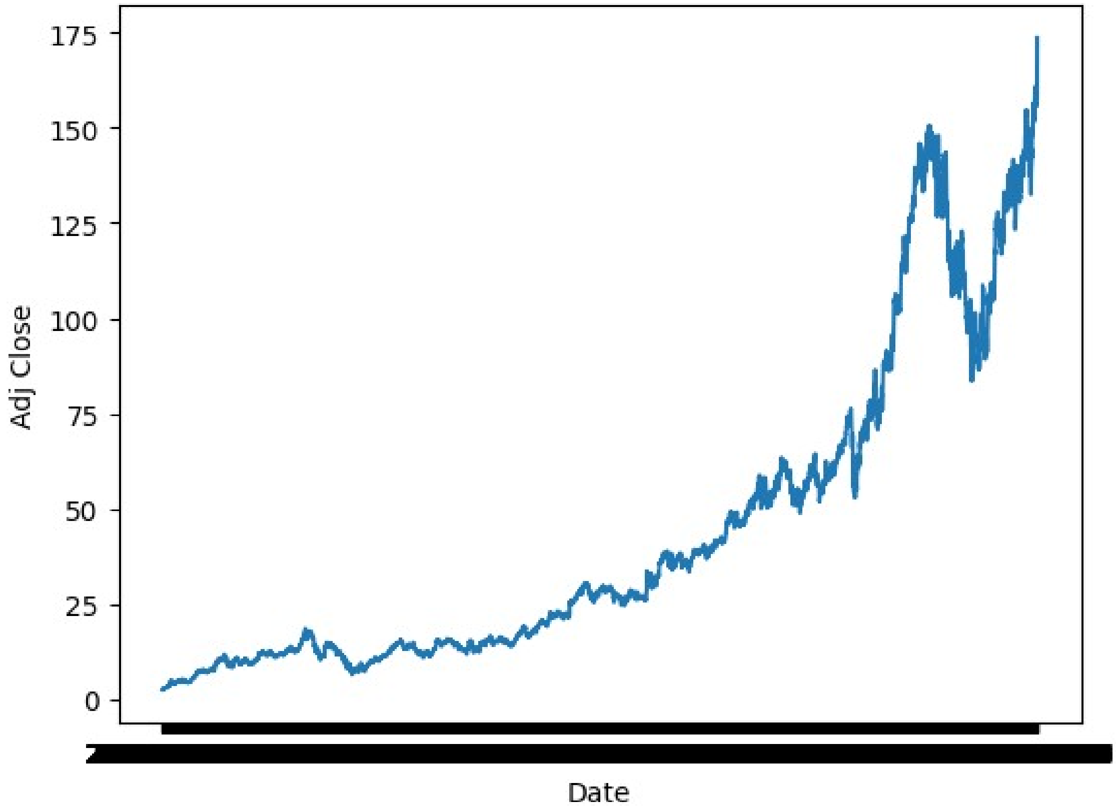
```python
import yfinance as yf
# data = yf.download('GOOG')

# download data from Yahoo Finance and save it as csv file
# data.to_csv('GOOG.csv')

# load data from csv file
import pandas as pd
data = pd.read_csv('GOOG.csv')
df = data.reset_index()
print(df.columns)
```

```
Index(['index', 'Date', 'Open', 'High', 'Low', 'Close', 'Adj Close',
'Volume'], dtype='object')
```

TASK-1: Plot the prices for the given data.

```python
import seaborn as sns
sns.lineplot(data=df, x='Date', y='Adj Close')
```

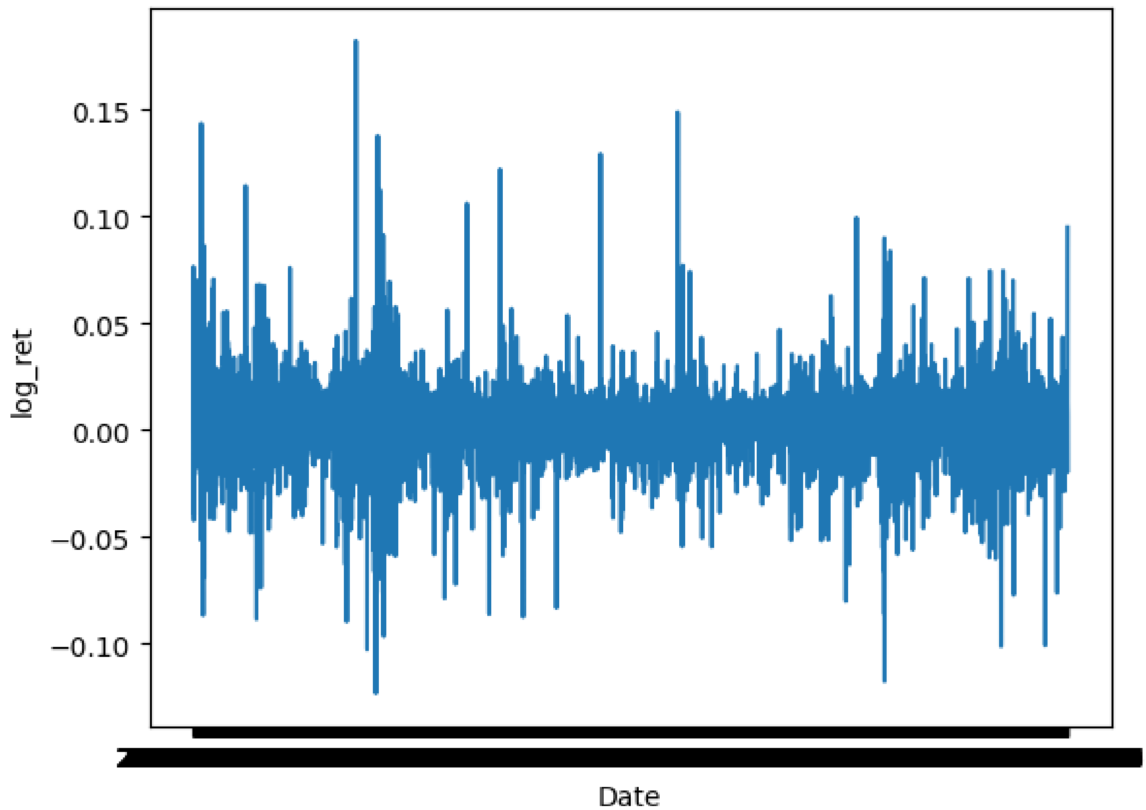
```
<Axes: xlabel='Date', ylabel='Adj Close'>
```



TASK-2: Plot log-returns for the given data.

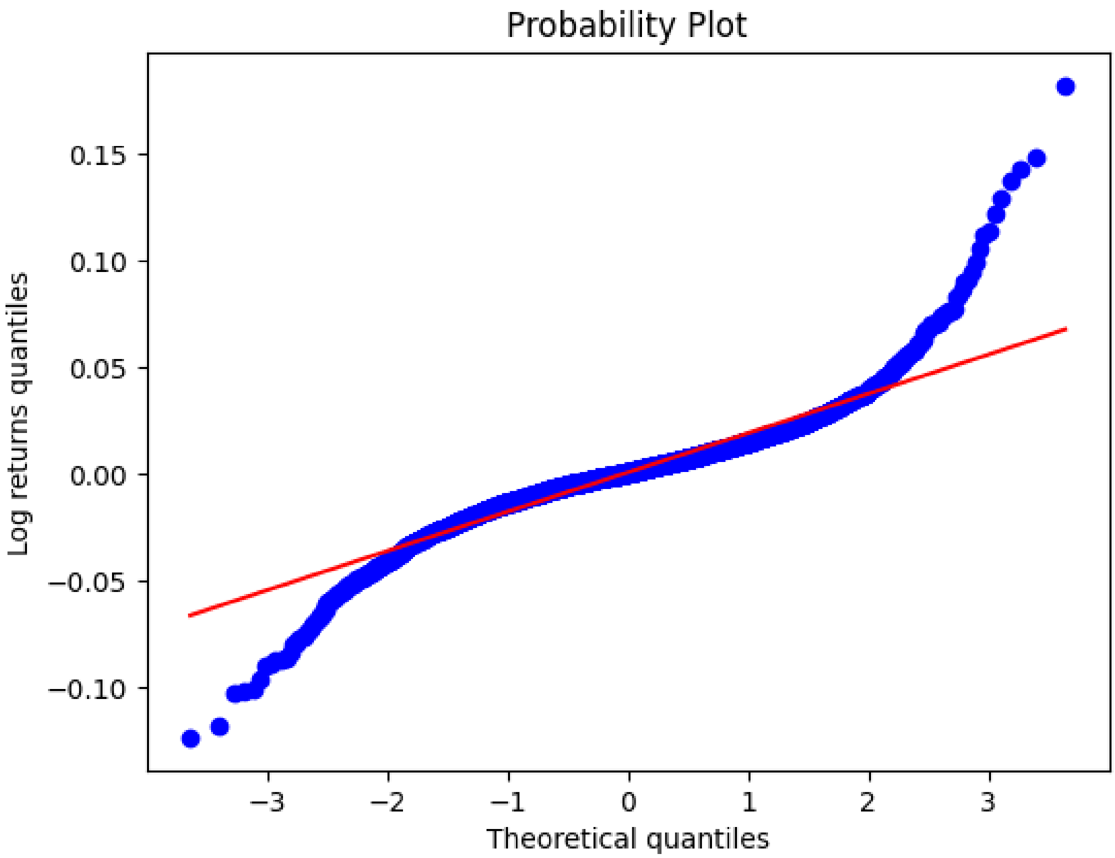
```python
import numpy as np
df['log_ret'] = np.log(df['Adj Close'] / df['Adj Close'].shift(1))
df.fillna({'log_ret': 0}, inplace=True)
import seaborn as sns
sns.lineplot(data=df, x='Date', y='log_ret')
```

```
<Axes: xlabel='Date', ylabel='log_ret'>
```

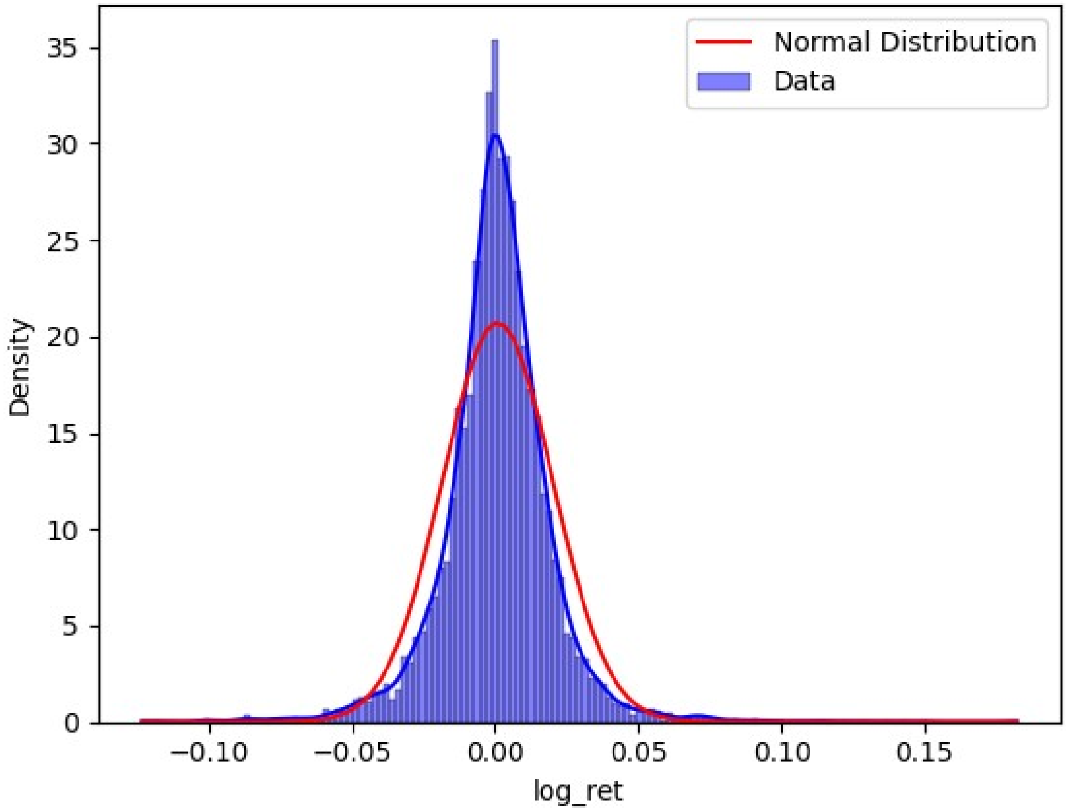


Task-3: Check whether log-returns are normally distributed using QQ plot,histogram and other statistical test like (Jerq-Berra, Kolmogorov-Smirnov test)

```
# check if the log returns are normally distributed using a Q-Q plot
import matplotlib.pyplot as plt
import scipy.stats as stats
stats.probplot(df['log_ret'], dist="norm", plot=plt)
plt.ylabel('Log returns quantiles')
plt.show()
```




```
# check if the log returns are normally distributed using histogram
sns.histplot(df['log_ret'], kde=True, stat='density', label='Data',
color='blue')

# plot the expected normal distribution
x = np.linspace(df['log_ret'].min(), df['log_ret'].max(), 100)
y = stats.norm.pdf(x, df['log_ret'].mean(), df['log_ret'].std())
plt.plot(x, y, label='Normal Distribution', color='red')

# Add a legend
plt.legend()

# Show the plot
plt.show()
```



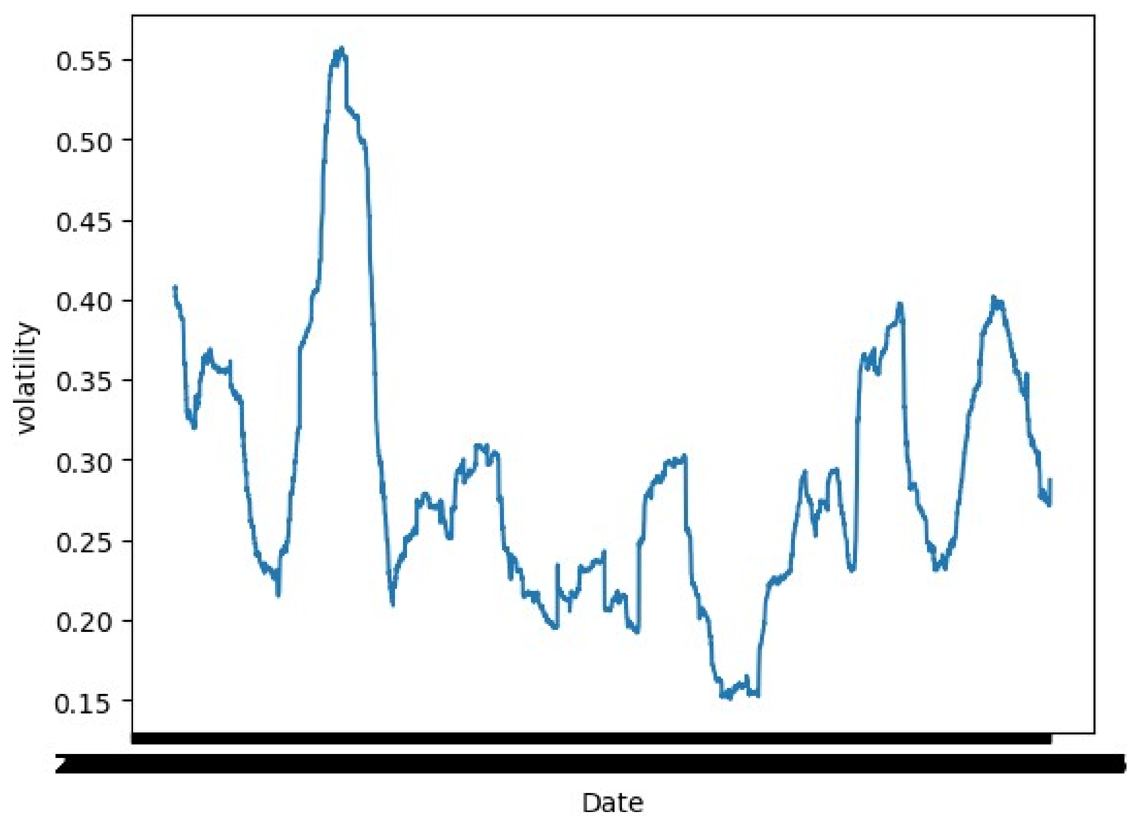
- As can be seen from the QQ plot, the log-returns are not normally distributed.
- The histogram also shows that the log-returns are not normally distributed.

```
# perform Jerq-Berra test for normality
jb_test = stats.jarque_bera(df['log_ret'])
print(f"jerq-Berra test: {jb_test}")
if jb_test.pvalue < 0.05:
    print('The log returns are not normally distributed')
else:
    print('The log returns are normally distributed')

jerq-Berra test: SignificanceResult(statistic=13329.95778158534,
pvalue=0.0)
The log returns are not normally distributed

# perform Kolmogorov-Smirnov test for normality
ks_test = stats.kstest(df['log_ret'], 'norm')
print(f"Kolmogorov-Smirnov test: {ks_test}")
if ks_test.pvalue < 0.05:
    print('The log returns are not normally distributed')
else:
    print('The log returns are normally distributed')

Kolmogorov-Smirnov test: KstestResult(statistic=0.46990310162587856,
pvalue=0.0, statistic_location=-0.05625188188628757, statistic_sign=-
```

```
1)
The log returns are not normally distributed
```

Task-4: Estimate the historical volatility using log returns.

```
# Estimate trend of annualized historical volatility using log
returns. (window = 252 days)
df['volatility'] = df['log_ret'].rolling(window=252).std() *
np.sqrt(252)
df['volatility'].dropna(inplace=True)
sns.lineplot(data=df, x='Date', y='volatility')
hist_vol = df['volatility'].iloc[-1]

# print the annualized historical volatility for last 252 days
print(f"Annualized Historical volatility: {hist_vol}")

Annualized Historical volatility: 0.2873627770614688
```



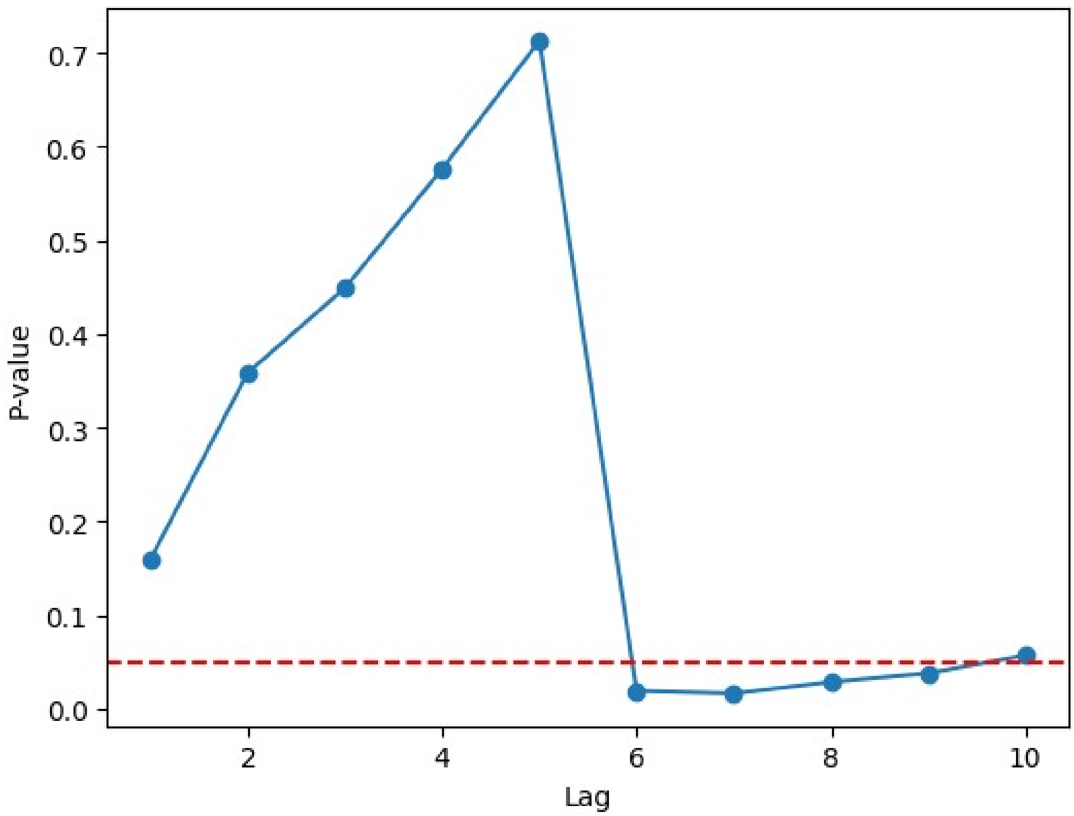
Task-5: Identify the risk free rate for the given currency (3-Months treasury rate for the currency

```
#Identify the risk free rate for USD (3-Months treasury rate for the
currency)
data = yf.download('^IRX',period='3m')
```

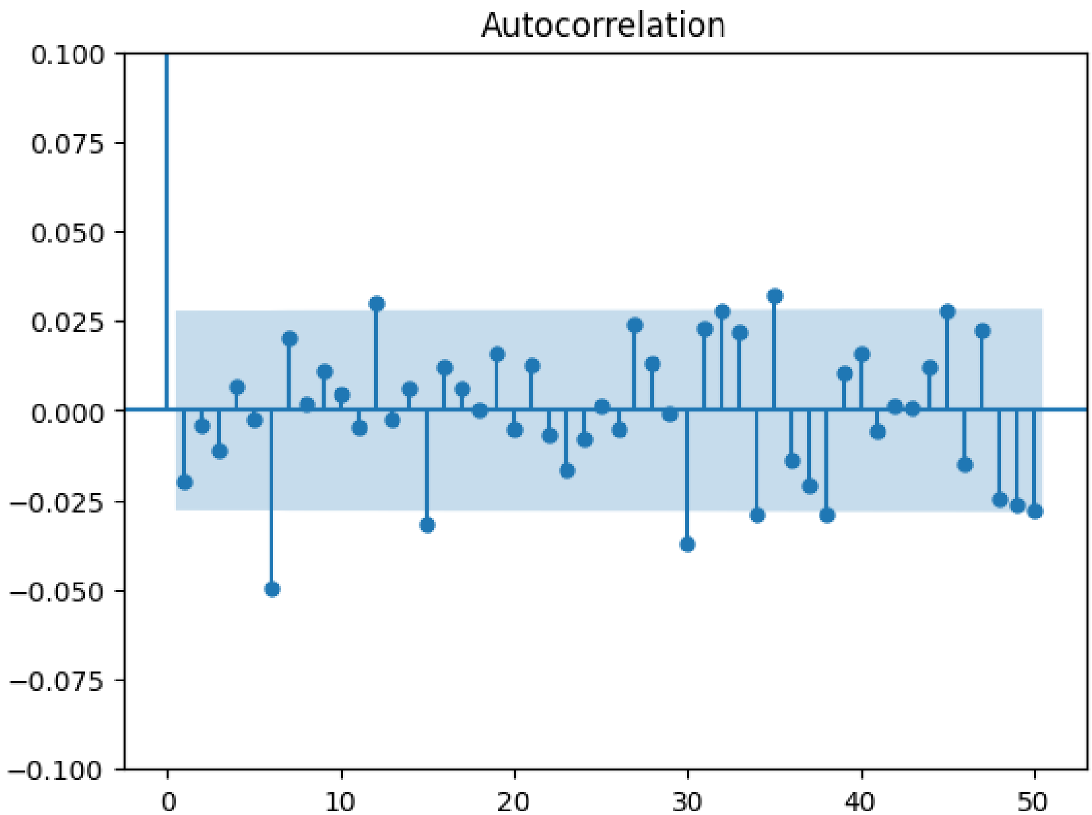
```
risk_free_rate = data['Adj Close'].mean() / 100
print(f"3 month risk free rate: {risk_free_rate*100}")
# risk_free_rate = 0.05238

[*********************100%%**********************]  1 of 1 completed

3 month risk free rate: 5.23799991607666
```

Task-6: Test the assumption if the log-returns are independent/uncorrelated.

```
# Ljung-Box Test: to check if the log returns are
independent/uncorrelated
from statsmodels.stats.diagnostic import acorr_ljungbox

lb_test = acorr_ljungbox(df['log_ret'], lags=10)

# Plot the p-values
plt.plot(lb_test.lb_pvalue, marker='o')
plt.axhline(0.05, color='red', linestyle='--')
plt.xlabel('Lag')
plt.ylabel('P-value')
plt.show()

# if any of the p-values is less than 0.05, the log returns are
autocorrelated
if any(lb_test["lb_pvalue"] < 0.05):
    print('The log returns are autocorrelated')
else:
    print('The log returns are not autocorrelated')
```




```
The log returns are autocorrelated

# using ACF plot
from statsmodels.graphics.tsaplots import plot_acf
plt.figure(figsize=(10, 2))
plot_acf(df['log_ret'], lags=50)
plt.ylim(-0.1, 0.1)  # Change the scale of the y-axis
plt.show()

<Figure size 1000x200 with 0 Axes>
```




```python
def runs_test(log_returns):
  """
  performs a Runs Test to assess independence in log returns.
  """
  n = len(log_returns)
  num_runs = 1  # Initialize number of runs

  # Iterate through log returns, checking for changes in sign
  for i in range(1, n):
    if log_returns[i] * log_returns[i-1] < 0:  # Check for sign change
      num_runs += 1

  # Calculate expected number of runs and standard deviation
  expected_runs = (2 * n - 1) / 3
  std_deviation = np.sqrt((16 * n - 29) / 90)

  # Calculate z-score
  z_score = (num_runs - expected_runs) / std_deviation

  return num_runs, expected_runs, std_deviation, z_score

_,_,_, z_score = runs_test(df['log_ret'])

print("Z-Score:", z_score)
```

```
if abs(z_score) > 1.96:
    print('The log returns are not independent/auto-correlated')
else:
    print('The log returns are independent')

Z-Score: -27.686669256786267
The log returns are not independent/auto-correlated
```

both run test, ACF plot and Ljung-box test shows that the log returns show correlation.

Task-7: Calculate the option price for an In-The-Money (ITM) European call option and In-The-Money European put option for the maturity May 31, 2024. The pricing date can be taken on which you calculate the option price.

```
import numpy as np
import math
# Base class for option pricing
class OptionPricing():
    def __init__(self, S, K_call,K_put, r, T, sigma):
        self.S = S
        self.K_call = K_call
        self.K_put = K_put
        self.r = r
        self.T = T
        self.sigma = sigma
    def call_price(self):
        pass
    def put_price(self):
        pass
    def price(self, option_type):
        if option_type == 'call':
            call_price =  self.call_price()
            return call_price
        elif option_type == 'put':
            put_price  = self.put_price()
            return put_price
        else:
            raise ValueError('Option type must be either "call" or
"put"')


# Black-Scholes model for option pricing
class BlackScholes(OptionPricing):
    def __init__(self, S, K_call,K_put, r, T, sigma):
        super().__init__(S, K_call,K_put, r, T, sigma)

    def call_price(self):
        self.d1 = (np.log(self.S / self.K_call) + (self.r + 0.5 *
```

```
self.sigma ** 2) * self.T) / (self.sigma * np.sqrt(self.T))
        self.d2 = self.d1 - self.sigma * np.sqrt(self.T)
        call = self.S * stats.norm.cdf(self.d1) - self.K_call *
np.exp(-self.r * self.T) * stats.norm.cdf(self.d2)
        return call

    def put_price(self):
        self.d1 = (np.log(self.S / self.K_put) + (self.r + 0.5 *
self.sigma ** 2) * self.T) / (self.sigma * np.sqrt(self.T))
        self.d2 = self.d1 - self.sigma * np.sqrt(self.T)
        put = self.K_put * np.exp(-self.r * self.T) * stats.norm.cdf(-
self.d2) - self.S * stats.norm.cdf(-self.d1)
        return put

# Binomial model for option pricing
class CRR(OptionPricing):
    def __init__(self, S, K_call,K_put, r, T, sigma,n):
        super().__init__(S, K_call,K_put, r, T, sigma)
        self.n = n
        self.dt = T / self.n # dt: Size of the time step
        self.u = math.exp(sigma * math.sqrt(self.dt)) # u: Factor by
which the stock price increases in each time step
        self.d = 1 / self.u # d: Factor by which the stock price
decreases in each time step
        self.p = (math.exp(self.r * self.dt) - self.d) / (self.u -
self.d) # p: Risk-neutral probability of a price increase
        self.prices = np.zeros((n + 1, n + 1)) # 2D array to store the
stock prices in the binomial tree
        self.prices[0, 0] = S

    def price(self, option_type):
        if option_type == 'call':
            return self.call_price(self.n)
        elif option_type == 'put':
            return self.put_price(self.n)
        else:
            raise ValueError('Option type must be either "call" or
"put"')

    def call_price(self, n=1000):
        return self.crr_option_price('call', n)

    def put_price(self, n=1000):
        return self.crr_option_price('put',n)

    def crr_option_price(self,option_type, n=1000):
        for i in range(1, n + 1):
            self.prices[i, 0] = self.prices[i - 1, 0] * self.u
            for j in range(1, i + 1):
                self.prices[i, j] = self.prices[i - 1, j - 1] * self.d
```

```
        option_prices = np.zeros((n + 1, n + 1))
        for j in range(n + 1):
            option_prices[n, j] = max(0, self.prices[n, j] -
self.K_call) if option_type == 'call' else max(0, self.K_put -
self.prices[n, j])
        for i in range(n - 1, -1, -1):
            for j in range(i + 1):
                option_prices[i, j] = math.exp(-self.r * self.dt) *
(self.p * option_prices[i + 1, j] + (1 - self.p) * option_prices[i +
1, j + 1])
        return option_prices[0, 0]

# Monte Carlo Simulation for option pricing
class SimulationPricing(OptionPricing):

    def __init__(self, S, K_call,K_put, r, T, sigma,n,
num_simulations):
        super().__init__(S, K_call,K_put, r, T, sigma,)
        self.n = n
        self.num_simulations = num_simulations
        self.T = T
        self.dt = T / self.n

    def call_price(self,display_graphs=False):
        return
self.simulate_call_option_price(display_graphs=display_graphs)

    def put_price(self, display_graphs=False):
        return
self.simulate_put_option_price(display_graphs=display_graphs)

    def price(self, option_type, display_graphs=False):
        if option_type == 'call':
            return self.call_price(display_graphs=display_graphs)
        elif option_type == 'put':
            return self.put_price(display_graphs=display_graphs)
        else:
            raise ValueError('Option type must be either "call" or
"put"')

    def simulate_call_option_price(self, display_graphs=False):
        prices = np.zeros((self.num_simulations, self.n + 1))
        prices[:, 0] = self.S
        for i in range(1, self.n + 1):
            z = np.random.normal(size=self.num_simulations)
            prices[:, i] = prices[:, i - 1] * np.exp((self.r - 0.5 *
self.sigma ** 2) * self.dt + self.sigma * np.sqrt(self.dt) * z)
        option_prices = np.maximum(0, prices[:, -1] - self.K_call)
        # also plot the price path for the first 40 simulations
```

```
        if display_graphs:
            for i in range(40):
                plt.plot(prices[i])
            plt.xlabel('Time Steps')
            plt.ylabel('Stock Price')
            plt.title('40 Stock Price Path for calculating call option
price')
            plt.show()
        return np.mean(option_prices) * np.exp(-self.r * self.T)

    def simulate_put_option_price(self, display_graphs=False):
        prices = np.zeros((self.num_simulations, self.n + 1))
        prices[:, 0] = self.S
        for i in range(1, self.n + 1):
            z = np.random.normal(size=self.num_simulations)
            prices[:, i] = prices[:, i - 1] * np.exp((self.r - 0.5 *
self.sigma ** 2) * self.dt + self.sigma * np.sqrt(self.dt) * z)
        option_prices = np.maximum(0, self.K_put - prices[:, -1])
        # also plot the price path for the first 40 simulations
        if display_graphs:
            for i in range(40):
                plt.plot(prices[i])
            plt.xlabel('Time Steps')
            plt.ylabel('Stock Price')
            plt.title('40 Stock Price Path for calculating put option
price')

            plt.show()
        return np.mean(option_prices) * np.exp(-self.r * self.T)



def getAnalysis(S, K_call,K_put, r, T, sigma):
    # CRR model
    n= 50
    crrOptionPricing = CRR(S, K_call,K_put, r, T, sigma, n)
    CRR_call_option_price = crrOptionPricing.price("call")
    print(f"CRR: Option price for an In-The-Money European call
option: {CRR_call_option_price}")
    CRR_put_option_price = crrOptionPricing.price("put")
    print(f"CRR: Option price for an In-The-Money European put option:
{CRR_put_option_price}")
    print()

    # Black-Scholes model
    bsOptionPricing = BlackScholes(S, K_call,K_put, r, T, sigma)
    BS_call_option_price = bsOptionPricing.price("call")
    print(f"BS Model: Option price for an In-The-Money European call
option: {BS_call_option_price}")
    BS_put_option_price = bsOptionPricing.price("put")
```

```
    print(f"BS Model: Option price for an In-The-Money European put
option: {BS_put_option_price}")
    print()

    # Monte Carlo Simulation
    num_simulations = 1000
    n_steps = 10000
    simulatedOptionPricing = SimulationPricing(S, K_call,K_put, r, T,
sigma, n_steps, num_simulations)
    simulated_call_option_price =
simulatedOptionPricing.simulate_call_option_price(display_graphs=True)
    print(f"Simulation: Option price for an In-The-Money European call
option: {simulated_call_option_price}")
    simulated_put_option_price =
simulatedOptionPricing.simulate_put_option_price(display_graphs=True)
    print(f"Simulation: Option price for an In-The-Money European put
option: {simulated_put_option_price}")
    print()

    # Create a DataFrame to display the option pricing data
    data = {'model': ['Black-Scholes', 'CRR', 'Simulation'],
        'call': [BS_call_option_price, CRR_call_option_price,
simulated_call_option_price],
        'put': [BS_put_option_price, CRR_put_option_price,
simulated_put_option_price]}
    option_pricing_data = pd.DataFrame(data)
    return option_pricing_data
```

Setup for the option pricing:

```
### SETUP ###
import datetime
import pandas as pd
S = df['Adj Close'].iloc[-1] # current stock price
K_call = 170 # strike price for call option
K_put = 180.00 # strike price for put option
r = risk_free_rate # 3m risk free rate for USD; (calculated in Task-6)
T = (datetime.datetime(2024, 5, 31) - datetime.datetime.now()).days /
365 # T is difference between the 31 may 2024 and the current date in
year
sigma = hist_vol # annualized historical volatility for last 252 days
print(f"Current stock price: {S}")
print(f"volatility: {sigma}")
print(f"r: {r}")
print(f"T: {T}")
print(f"K_call: {K_call}")
```

```
print(f"K_put: {K_put}")
```

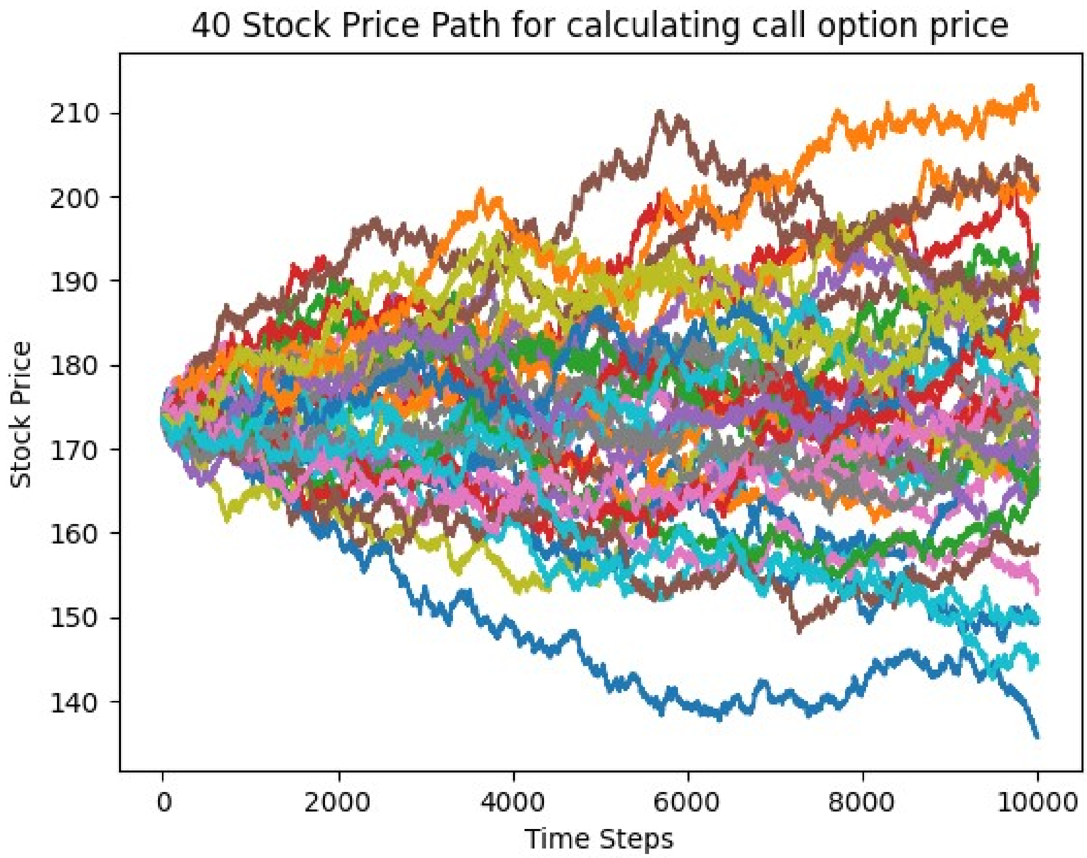
```
Current stock price: 173.69000244140625
volatility: 0.2873627770614688
r: 0.052379999160766605
T: 0.09041095890410959
K_call: 170
K_put: 180.0
```

Pricing using Historical Volatility

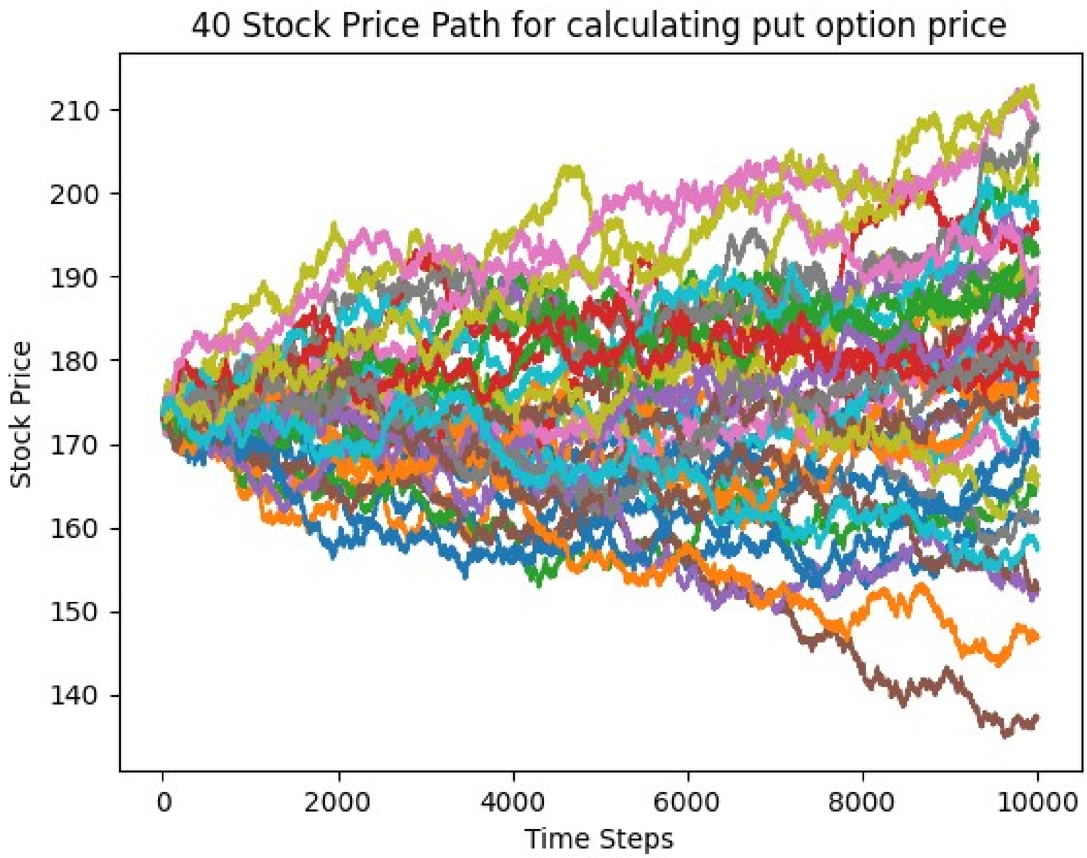
option price comparison between CRR, Black-Scholes and Simulation method.

```
option_pricing_data_historical =  getAnalysis(S, K_call,K_put, r, T,
sigma)
option_pricing_data_historical
```

```
CRR: Option price for an In-The-Money European call option:
8.420028198233364
CRR: Option price for an In-The-Money European put option:
9.220724627927

BS Model: Option price for an In-The-Money European call option:
8.424078225057286
BS Model: Option price for an In-The-Money European put option:
9.194815005768774
```




```
Simulation: Option price for an In-The-Money European call option:
8.586471566963915
```




```
Simulation: Option price for an In-The-Money European put option:
9.220209005662515


             model      call       put
0  Black-Scholes  8.424078  9.194815
1            CRR  8.420028  9.220725
2     Simulation  8.586472  9.220209
```

Task-8: We have reserved 3 marks for using other methods to estimate the volatility like GARACH or Stochastic volatility methods.

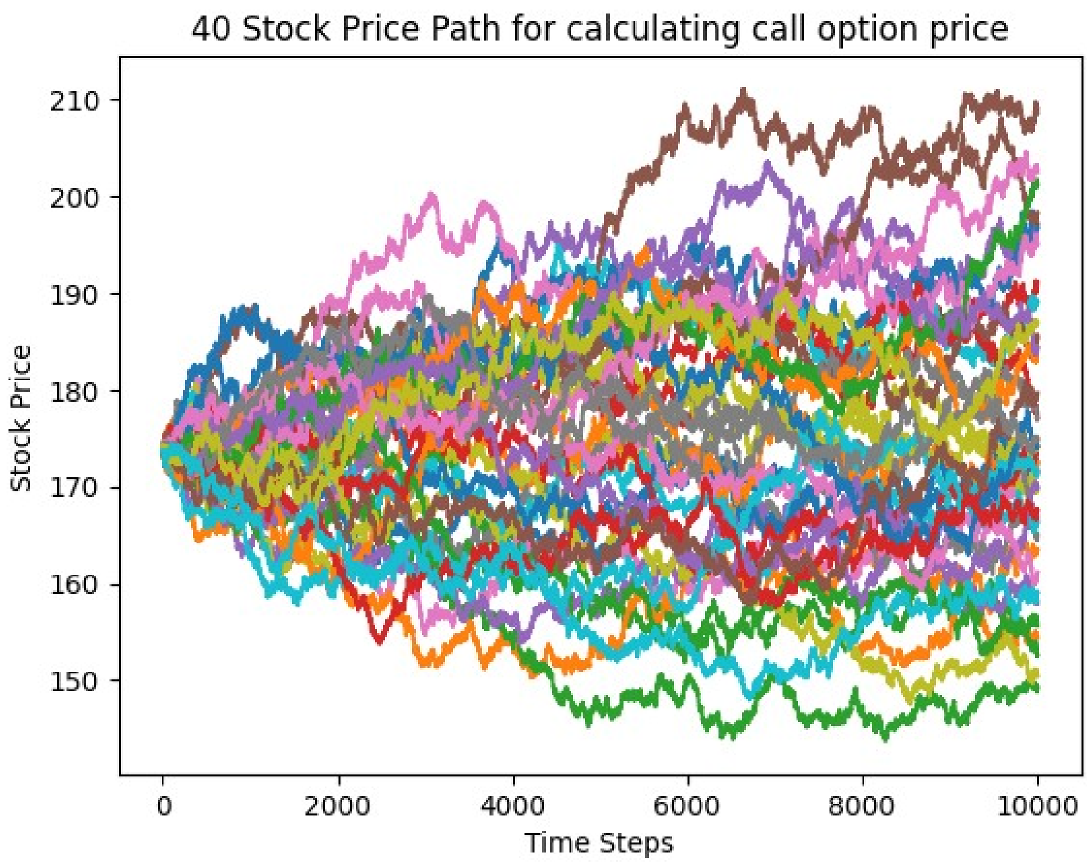
```
# estimate implied volatility using GARACH method
import matplotlib.pyplot as plt
from pmdarima.model_selection import train_test_split

from arch import arch_model
returns = df['log_ret'].dropna()
returns_rescaled = 10 * returns
model = arch_model(returns_rescaled, vol='GARCH', p=1, q=1,
rescale=False)
results = model.fit(disp='off')
```

```
# Get conditional volatility forecast
forecast_volatility = results.forecast(horizon=1).variance.iloc[-1, 0]
forecast_volatility = np.sqrt(forecast_volatility)
print(f"Forecasted volatility: {forecast_volatility}")
print(f"Historical volatility: {hist_vol}")
```

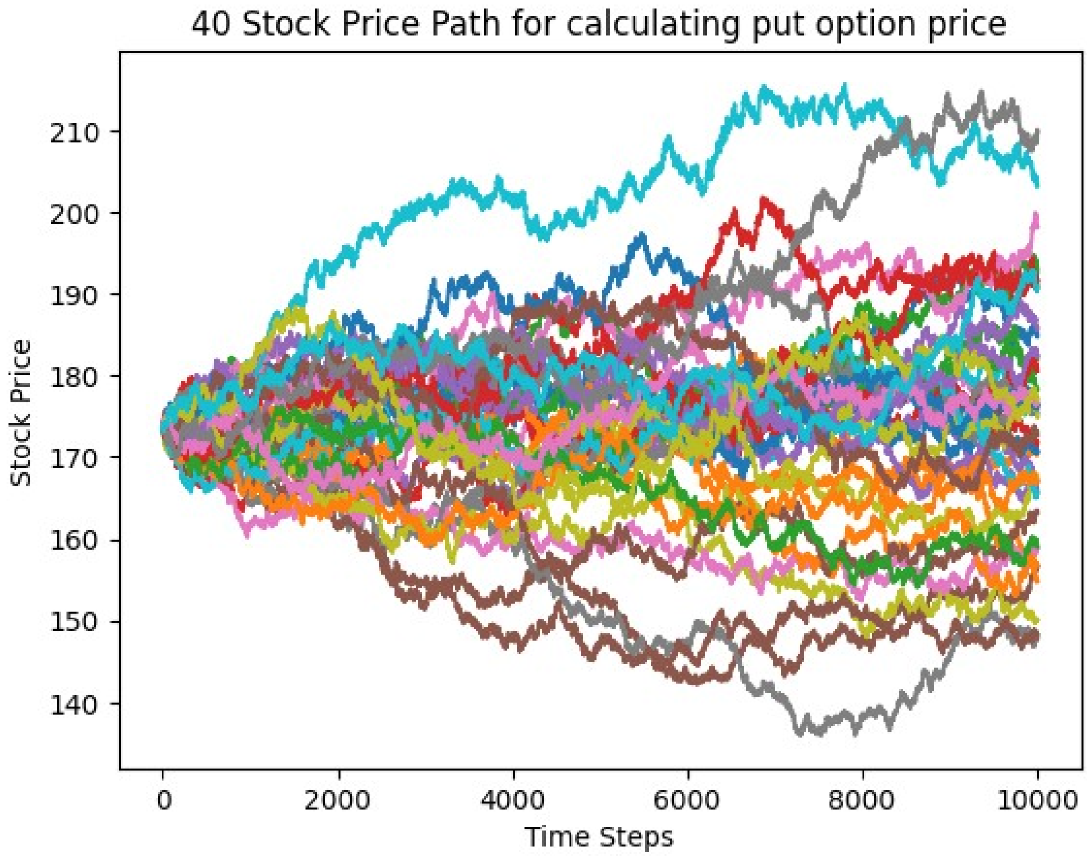
```
Forecasted volatility: 0.2899623910268287
Historical volatility: 0.2873627770614688
```

```
option_pricing_data_implied = getAnalysis(S, K_call,K_put, r, T,
forecast_volatility)
option_pricing_data_implied
```

```
CRR: Option price for an In-The-Money European call option:
8.472379273757484
CRR: Option price for an In-The-Money European put option:
9.272269231986943

BS Model: Option price for an In-The-Money European call option:
8.475105638844099
BS Model: Option price for an In-The-Money European put option:
9.246386127291416
```



```
Simulation: Option price for an In-The-Money European call option:
9.300908167545634
```




```
Simulation: Option price for an In-The-Money European put option:
8.691826592688791


            model      call       put
0   Black-Scholes  8.475106  9.246386
1             CRR  8.472379  9.272269
2      Simulation  9.300908  8.691827

# create a table to compare option pricing using historical and
implied volatility
print(f"sigma: {hist_vol}")
print(f"Current stock price: {S}")
print(f"risk free rate: {r}")
print(f"T: {T}")
print(f"K_call: {K_call}")
print(f"K_put: {K_put}")
print(f"Forecasted volatility: {forecast_volatility}")
option_pricing_data = pd.concat([option_pricing_data_historical,
option_pricing_data_implied], keys=['using Historical volatility',
```

```
'using Implied volatility'])
option_pricing_data
```

```
sigma: 0.2873627770614688
Current stock price: 173.69000244140625
risk free rate: 0.052379999160766605
T: 0.09041095890410959
K_call: 170
K_put: 180.0
Forecasted volatility: 0.2899623910268287
```

```
                                        model      call       put
using Historical volatility 0   Black-Scholes  8.424078  9.194815
                            1             CRR  8.420028  9.220725
                            2      Simulation  8.586472  9.220209
using Implied volatility    0   Black-Scholes  8.475106  9.246386
                            1             CRR  8.472379  9.272269
                            2      Simulation  9.300908  8.691827
```

Results

Option Pricing Parameters

Parameter	Value
sigma (Historical volatility)	0.2873627770614688
S0 (Spot Price)	173.69000244140625
r (Risk-Free Rate)	0.052379999160766605
T (Time to Maturity)	0.09041095890410959
K_call (Strike Price - Call)	170
K_put (Strike Price - Put)	180.0
sigma_hat (Forecasted Volatility)	0.2899623910268287

Option Pricing Results

Model	volatility type	call	put
Black-Scholes	Historical	8.424078	9.194815
CRR	Historical	8.420028	9.220725
Simulation	Historical	8.417756	9.330980
Black-Scholes	Forecasted	8.475106	9.246386
CRR	Forecasted	8.472379	9.272269
Simulation	Forecasted	8.402203	9.112247

- simulation results can vary due to the random nature of the simulation.